Currency Crisis Prediction using Decision Trees

Victor Zeng Sean Burgess

April 2020

1 Introduction

Decision trees are one of the most popular and wildly used models for classification. They work by recursively splitting a dataset based on the values of individual attributes. At each node in the tree, it chooses the decision criteria which maximize the information gain of the resulting split. In this project, we attempt to use decision trees to predict currency crises, which Reinhart and Rogoff defines as a drop of 15% in the value of a country's currency relative to some anchor currency, in rich countries.

2 Data

We downloaded time-series for 42 indicators for Canada, France, Germany, Italy, Japan, the United Kingdom, the United States, Norway, Switzerland, Sweden, Finland, Denmark, Austria, and Ireland from the World Development Indicators and combined them with the financial crises data from Reinhart and Rogoff. We then used pandas to eliminate 18 indicators for which we had less than 200 country-years of data, leaving us with 23 indicators for classification (we list these indicators in Appendix A). We then eliminate country-years for which complete data was not available, leaving us with data from years 1972 to 2010.

3 Classification

We then trained fine, medium, and coarse decision trees in MATLAB on the data collected and evaluated them using 5-fold cross validation. Our best model, the coarse tree, produced an accuracy of 91.8%, but the fine and medium trees with an accuracy of 86.9% were not very far behind.

4 Discussion

4.1 Classification Performance

Due to the high level of imbalance in the data, accuracy is not a good metric for evaluating classification performance; a naive classifier which always predicts no crisis would achieve 92.9% accuracy. Two better metrics for determining the performance are the geometric mean of the model's class-wise accuracies (G-mean) and the area under the ROC curve (AUC).

$$\text{G-mean} = \sqrt{\frac{TP}{TP+FN} \cdot \frac{TN}{TN+FP}}$$

The G-mean is essentially a more balanced version of accuracy, while the AUC measures the probability of correctly discriminating between a randomly selected positive and a randomly selected negative point. Like accuracy, both the metrics range from 0 to 1, with higher scores being better. However, unlike accuracy, they are not affected by class-imbalance in the test set.

Our best classifier, the coarse tree, manages to achieve a g-mean of 34.9% and an AUC of 0.55, meaning that our model barely outperforms a classifier that randomly guesses (an uninformed classifier would achieve a AUC of 0.5). Looking at the scatter plot in Figure 1, we can see the reason for such abysmal performance; there is no easily drawn boundary between crises and normal data points.

4.2 Classification Criteria

Looking at the classification tree, we see that the most important variables used in predicting the type of crisis are gross domestic savings, general government final consumption expenditure, foreign direct investments net outflows, and GDP growth.

Likewise, in the right sub-tree, we see that a high level of foreign capital outflows predicts a currency crisis. This makes intuitive sense, as high capital outflows increase the supply of a country's currency in the foreign exchange markets, putting downwards pressure on a country's currency price. Likewise, high capital outflows might indicate instability within a country, further discouraging investors. If this is the case, then it will put additional downward pressure on the currency's price through the demand side.

On the left sub-tree, we see that a high level of government consumption expenditure is a predictor of a currency crisis. This is a bit harder to explain, as there is no direct relationship between government expenditure and the foreign exchange market. However, high government expenditure can incentivize a country to debase its currency. This in turn can cause an inflation crisis, and with it an accompanying currency crisis.

5 Alternative Classifiers

We also try using a 1-nearest-neighbor classifier, which works by storing the training data and assigning the class of the nearest neighbor of the input point, from sci-kit learn. Like with the decision tree-classifier, we evaluate the nearest-neighbor classifier though 5-fold cross validation. We find that it manages to achieve a 37.27% g-mean score, and a 0.569 AUC score, which is a slight improvement over the performance than the decision tree classifier. However, we do not believe that this performance improvement is statistically significant, and the nearest-neighbor classifier lacks the explainability of a decision tree.

6 Figures

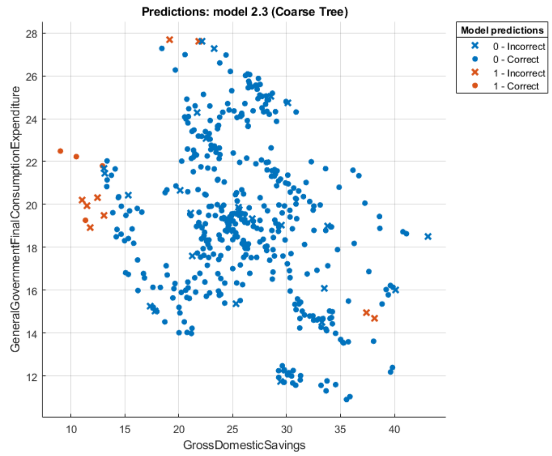

Figure 1: Scatter plot of two most important classes.

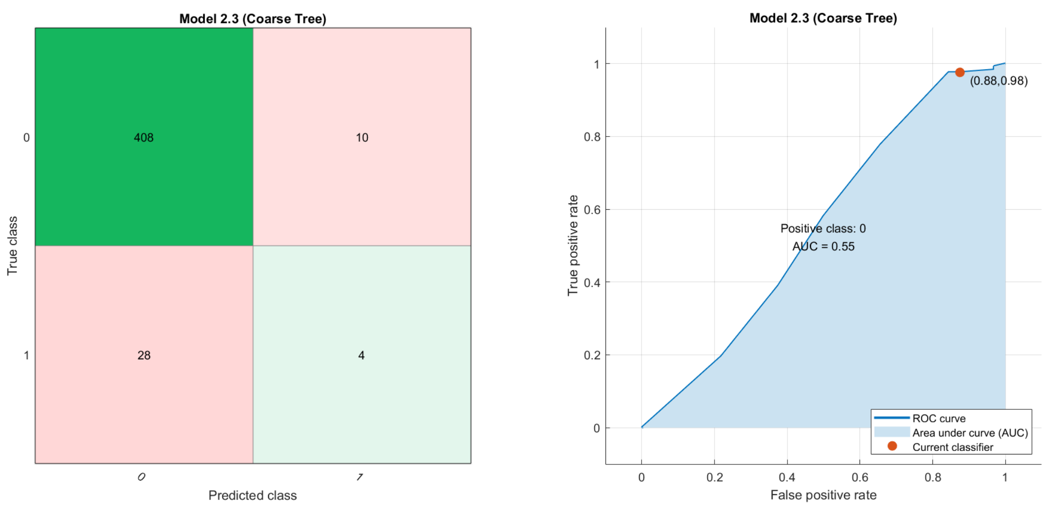

Figure 2: Performance of the coarse tree classifier

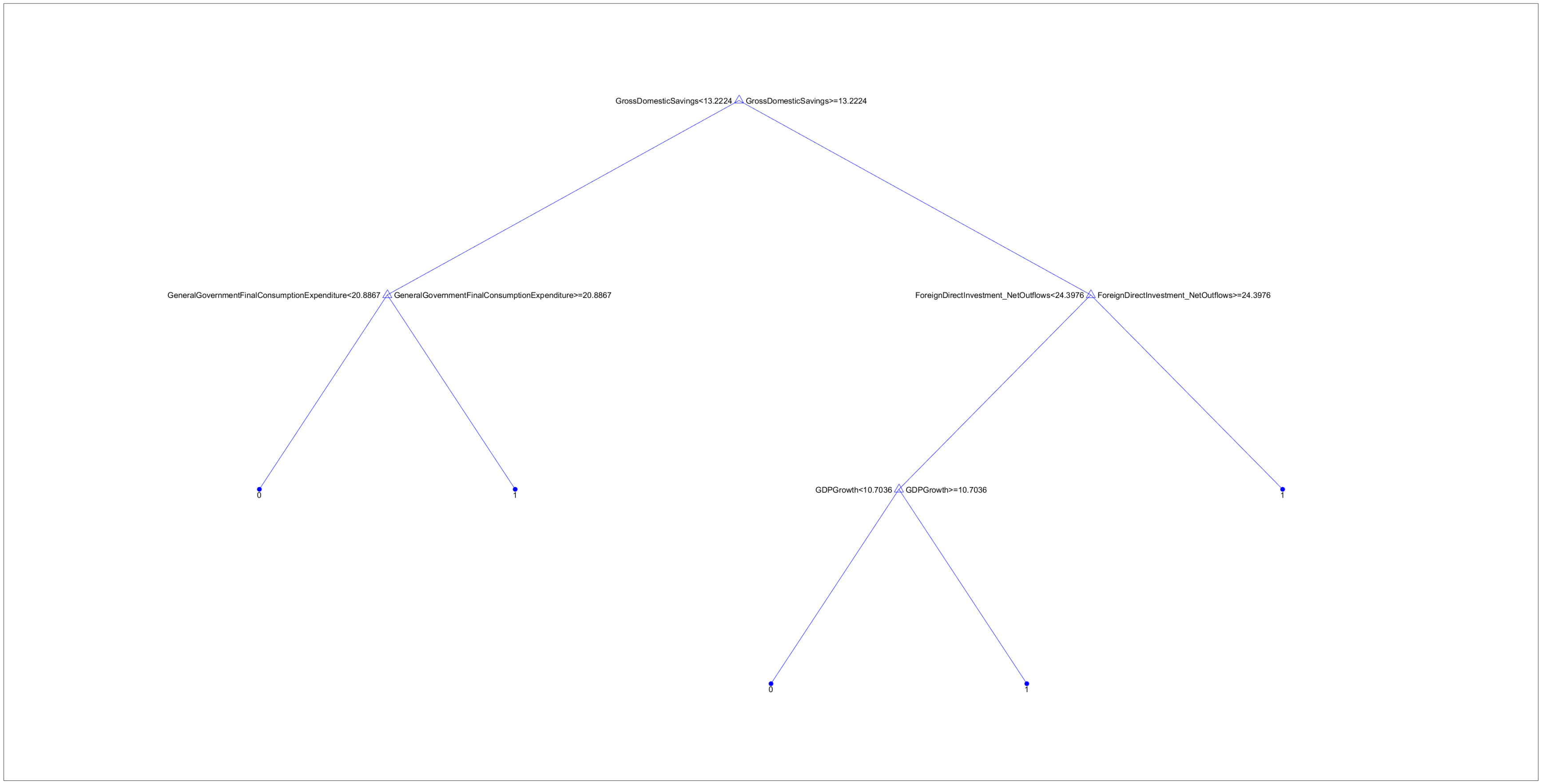

Figure 3: Highest accuracy tree classifier

Appendices

A Indicators Used

1. GDP growth (annual %)
2. GDP per capita (current US$)
3. Foreign direct investment, net outflows (% of GDP)
4. Exports of goods and services (% of GDP)
5. General government final consumption expenditure (% of GDP)
6. Gross domestic savings (% of GDP)
7. Inflation, GDP deflator (annual %)
8. Tax revenue (% of GDP)
9. Trade (% of GDP)
10. External balance on goods and services (% of GDP)
11. Foreign direct investment, net inflows (% of GDP)
12. GDP per capita growth (annual %)
13. GDP per capita (constant 2010 US$)
14. Gross fixed capital formation (% of GDP)
15. Gross capital formation (% of GDP)
16. Gross national expenditure (% of GDP)
17. Gross value added at basic prices (GVA) (constant 2010 US$)
18. Households and NPISHs final consumption expenditure (% of GDP)
19. Natural gas rents (% of GDP)
20. Revenue, excluding grants (% of GDP)
21. Unemployment, total (% of total labor force) (national estimate)
22. Total reserves (includes gold, current US$)
23. Inflation, consumer prices (annual %)